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IMPROVING THE NAVY NURSE CORPS' WARTIME SURGE FORCE PLANNING BY IMPLEMENTING A MARKOV MODEL

by

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One of the key components of Navy Medicine is the Navy Nurse Corps (NC). The commitment by the NC to be in sync with the Chief of Naval Operations' and Commandant of the Marine Corps' operational plans requires the Nurse Corps community to allocate subspecialties according to the needs of the Navy with the mindset of operational readiness. Under the current system of accession, the NC is meeting its targeted end strength (E/S). At the same time, however, the NC suffers from an imbalance in the management of its quality, the subspecialties (SSP): critical wartime subspecialties are understaffed, while the specialties fulfilling non-operational requirements are overstaffed. This accession practice results in an undersupply of critical SSPs should a contingency arise. This thesis therefore proposes a Markov model to optimize the surge force planning for the NC to maximize the probability that enough personnel will be available in critical SSPs to meet operational needs during a contingency. This model is designed to forecast future E/S and operational surge forces to assess whether they will meet the operational readiness goals from the National Defense Strategy. Based on hypothetical target E/S and beginning inventory, the model demonstrates reliable forecasting capabilities as it satisfied all three assumptions required to build a Markov model, demonstrating an almost identical behavior both by the fixed inventory accession and by the steady state method.

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One of the key components of Navy Medicine is the Navy Nurse Corps (NC). The commitment by the NC to be in sync with the Chief of Naval Operations' and Commandant of the Marine Corps' operational plans requires the Nurse Corps community to allocate subspecialties according to the needs of the Navy with the mindset of operational readiness. Under the current system of accession, the NC is meeting its targeted end strength (E/S). At the same time, however, the NC suffers from an imbalance in the management of its quality, the subspecialties (SSP): critical wartime subspecialties are understaffed, while the specialties fulfilling non-operational requirements are overstaffed. This accession practice results in an undersupply of critical SSPs should a contingency arise. This thesis therefore proposes a Markov model to optimize the surge force planning for the NC to maximize the probability that enough personnel will be available in critical SSPs to meet operational needs during a contingency. This model is designed to forecast future E/S and operational surge forces to assess whether they will meet the operational readiness goals from the National Defense Strategy. Based on hypothetical target E/S and beginning inventory, the model demonstrates reliable forecasting capabilities as it satisfied all three assumptions required to build a Markov model, demonstrating an almost identical behavior both by the fixed inventory accession and by the steady state method.

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LIST OF ACRONYMS AND ABBREVIATIONS

BA	Authorized Billets
BDCP	Baccalaureate Degree Completion Program
BUMED	Bureau of Medicine and Surgery
BUMIS	BUMED, Manpower Information System
CMC	Commandant of Marine Corps
CNO	Chief of Naval Operations
DA	Direct Accessions
DHA	Defense Health Agency
DMDC	Defense Manpower Data Center
DoD	Department of Defense
E/S	end-strength
FTOS	Full-Time Out-Service Training
FY17 NDAA	Fiscal Year 2017 National Defense Authorization Act
GME	Graduate Medical Education
HSCP	Health Services Collegiate Program
IDA	Institute for Defense Analyses
MECP	Medical Enlisted Commissioning Program
MTFs	Military Treatment Facilities
NC	Navy Nurse Corps
NCP	Nurse Candidate Program
NDAA	National Defense Authorization Act
NDS	National Defense Strategy
NROTC	Naval Reserve Training Corps
OPLANS	Operational Plans
SSP	Subspecialties
USN	United States Navy

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I. INTRODUCTION AND SIGNIFICANCE OF STUDY

Navy Medicine is committed to providing preventative care to its beneficiaries and to caring for its injured sailors and marines, "from the point of injury on the battlefield to comprehensive rehabilitative care [at] the [bedside, as well as to] supporting contingency, humanitarian, and joint operations around the world" (*Ensuring Medical Readiness*, 2016, p. 9). All these tasks link to our nation's strategic priorities: as Rear Admiral Moulton, MSC, USN, has emphasized, "the core mission of the Navy Medicine is inextricably linked with those we serve, the United States Navy (USN) and United States Marine Corps (USMC)" (*Ensuring Medical Readiness*, 2016, p. 2). Admiral Moulton continues by saying that that to "be fully engaged with supporting our maritime strategy [requires keeping] sailors and marines healthy and ready to deploy, as well as [delivering] world-class care, anytime, anywhere" (p. 2).

One of the key components of Navy Medicine is the Navy Nurse Corps (NC). The NC supports the Navy and Marine Corps' warfighting capability by providing cost-effective, high-quality care to active duty and retired service members and their families. To provide this level of care, nurses need to acquire training, education, and proficiency in various subspecialties (SSPs). Six of these subspecialties are identified by the NC as critical SSPs vital to accomplishing the wartime mission: Medical/Surgical (1910), Critical Care (1960), Peri/Op (1950), Emergency/Trauma (1945), Anesthesia (1972) and Mental Health Provider (1973) (Kinstler & Johnson, 2005). These critical SSPs make up the surge force inventories in the NC and are needed for up-tempo operational readiness in direct support of the Chief of Naval Operations' (CNO) and the Commandant of Marine Corps' (CMC) operational or theatrical contingencies.

The commitment by Navy Medicine and the NC to be in sync with the CNO and CMC's operational plans requires the Nurse Corps community to allocate subspecialties according to the needs of the Navy with the mindset of operational readiness. The current accession or recruiting pipelines utilized for producing new nursing graduates are the Direct Accessions (DA), Recalls, and other training pipelines like the Naval Reserve

Training Corps (NROTC), Nurse Candidate Program (NCP), or Medical Enlisted Commissioning Program (MECP).

NROTC, NCP, and MECP graduates are brand new nurses and labeled as generic professionals, coded as 1900. The majority of nurses who are coded 1900 are made up of these newly minted nurses, while a small portion of 1900 billets consists of those who are in transit, such as active duty nurses receiving Graduate Medical Education or training or active duty nurses on sick leave. The brand-new nurses all go through nursing internship programs before transitioning into other specialty codes and gaining their new SSP. Accession via the training pipelines is limited to the total number of congressionally authorized billets (BA). “Only authorized billets, not requirements, send demand signals to the military accession, education, training and distribution system” (Department of the Navy [DoN], 2015, p. 10). The new (1900) nurses each need time to get trained to fill an SSP according to the needs of the Navy.

When the training pipelines are inadequate to meet the end strength needs, the DA and Recalls accession sources are used as a valve system. The valve system incorporates the DA and Recalls, which allows NC personnel managers to meet the targeted End-Strength (E/S), or total number of personnel permitted by the BA each year, as well as to ensure that the NC has enough quality—i.e., enough trained nurses in each SSP to meet operational and non-operational requirements. The valve system allows NC manpower planner to pick and choose different ranks as well as specialties based on individuals’ accumulated skills and education level to fill the gaps not achieved through the training pipelines.

A. PROBLEM

Under this system of accession, the NC is currently meeting its targeted E/S, fielding 96% of Congress’ authorized billet (BA) (H. Ray, spreadsheet data email to author, November 13, 2018). At the same time, however, the NC suffers from an imbalance in the management of its quality, the subspecialties (SSP). Per the spreadsheet obtained from CDR Ray, critical wartime subspecialties (i.e., requirements to staff deployable specialties) are understaffed, while the specialties fulfilling non-operational requirements are overstaffed. In other words, too many nurses are being trained on non-critical SSPs during peacetime; likewise, too many new nurses are accessioned each year directly from the training pipeline—brand new nurses needing more training before they can be managed under a specific SSP group. This accession practice results in an undersupply of critical SSPs should a contingency arise.

A study by the Institute for Defense Analyses (IDA) that examines the total force mix within entire DoD medical community (i.e., not just the Navy NC) finds that the primary cause of understaffing of wartime subspecialties requirements could be because MTFs do not have enough patient acuity, which limits nurses' ability to maintain clinical skills (Whitley, Gould, Huff, & Wu, 2014). There is not enough beneficiary care workload for nurses in these facilities to train in preparation for potential operational needs. Operational medical force training is therefore limited by beneficiary care requirements.

Manpower practitioners in the NC are feeling the effects of the imbalance in SSPs indicated in the spreadsheet data. The NC Manpower and Navy Medicine's Business specialty leader, CDR H. Ray, organizes monthly Manpower voice-calls. The purpose of the monthly calls is to share knowledge and new policies among the practitioners. In an official email to the group following one of these meetings (February 1, 2019) CAPT Valerie Morrison puts forth ideas that "the old practice of balancing our operational needs against the beneficiary care-requirements should be put to rest; instead, we need to adhere what our National Defense Strategy needs are." Another Navy NC Manpower Analyst, CDR Robert Johns, who works at BUMED, Navy Medicine, in the Total Force/Human Resource Manpower (M1/M12) office, likewise expresses his concerns to the group, saying that, "these imbalances in the mix of skills in the NC will be felt to a greater degree over the next few years. This intensified impact is due to increased emphasis on operational readiness per the new National Defense Strategy" (R. Johns, email to author, February 2, 2019). This emphasis on operational readiness intensifies the NC's need for more accurate Manpower planning.

Currently, the Medical Manpower All Corps Requirements Estimator (MedMACRE) is the tool used to determine the NC's staffing needs. This thesis proposes a Markov Model that forecasts surge force planning using a continuous chain of estimations based on an initial inventory to predict the annual end strength of the NC system.

B. IMPORTANCE

Having the right quantity *and* right quality NC for the right jobs—ashore, onboard ships, under the sea, at the battlefield, and in the air or on the ground during a Medical Evacuation (MedEvac) transportation or transitional care—plays an integral part in Navy Medicine's success. Because of such successes, provided by highly qualified nurses and other medical professionals, the wartime surge force will likely continue to face increased demand. The IDA researchers Whitley et al. (2014) note, "The deployment requirement was a smaller medical footprint in theaters compared to any other wars before" (p. v). Despite this smaller medical footprint, the Operation Enduring Freedom/Operation Iraqi Freedom (OEF/OIF) data gives a better result than any other wars before—i.e., more lives saved. One reason for the better outcomes despite the smaller footprint was the highly specialized capabilities of the nurses and other medical personnel. At the same time, however, based on data covering FY2003–12, these researchers document that critical wartime inventories of subspecialties (SSPs) were understaffed across all service branches: Air Force, Army, and Navy Medicine. The practice of highly specializing to provide a high capability in the theater environment will very likely continue but compensating for understaffing with highly specialized personnel only goes so far; as the operational goals set forth in the NDAA increase demand for critical wartime inventories, the NC needs both quantity and the quality to accomplish the mission.

In addition, it is very likely that the current imbalance in manpower is resulting in a suboptimal use of funds. Optimization of required wartime SSPs E/S could therefore produce more efficiency within a constrained defense budget.

C. RESEARCH OBJECTIVES

Despite the small size of the naval medical strategic force, its manpower planning is very complex. The more complex the system is, the greater demand it produces for correct and successful force planning. This thesis therefore proposes more precise ways to optimize the surge force planning for the Navy Nurse Corps (NC) to maximize the probability that enough personnel will be available in critical SSPs to meet operational needs during a contingency. The objective of this thesis is to build a Markov model to forecast future E/S and operational surge forces to assess whether they will meet the operational readiness goals from the National Defense Strategy (NDS). This model is used to forecast a balanced mix of NC surge forces over the next *six* years in planning. The Markov model is then utilized in a fixed inventory equation to determine the number of personnel required to meet the target aggregate E/S of the six critical operational SSPs.

The Markov model can thus assist in managing NC personnel and can help in making recommendations for a strategically sound proportion of operational and non-operational forces.

D. THESIS ORGANIZATION

The remainder of this thesis is divided into five chapters. Chapter II gives a broad overview of Navy Medicine and examines how the DoD Health System's Platform Realignment into the DHA is a possible reason for the skill imbalance in the NC. Chapter III provides a literature review on the utilization of the Markov model and conceptual framework. Chapter IV describes data and methodology. Chapter V describes the implementation of the model and conducts an aggregate and a subspecialty level analysis. In addition, this chapter discusses limitations on the analysis. Chapter VI concludes with a summary and future study recommendations based on these results.

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II. INSTITUTIONAL BACKGROUND

Manpower planning entails forecasting the right number and quality of people at the right place and time. Constructing a Markov model of NC SSP requires considering of the current NC system's behavioral trends and various categories of the systems- different SSPs within the NC Organization. This chapter therefore provides a description of how a billet (i.e., a Navy job position) becomes authorized (funded); explains the current method of modeling the NC's Manpower requirement; and analyzes the possible sources of the suboptimal SSP distribution in the NC.

A. AUTHORIZED BILLET (BA)

According to the Operational Navy Instruction 1000.16 (OPNAVINST 1000.16), Authorized Billets (BA) are those faces—current inventory of personnel—that are supported by resources (i.e., funded) (DoN, 2015). Per OPNAVINS 1000.16 and Rodney (2017), each billet in the Navy is a job position described by a unique unit identification code (UIC) that is usually filled by personnel possessing the authorized grade, designator, and sometimes secondary expertise required for a billet. There are seven authorized grades for the nurse corps: O-1 to O-7. The primary expertise required for the nursing billet is 2900, a designator. Some billets require more specialized skills than are defined by a designator; these types of secondary expertise required for a billet are called additional qualification designators (AQDs). The billets become authorized when Congress provides funding for them. In Manpower planning, BA is the target that personnel planners endeavor to meet (Rodney, 2017).

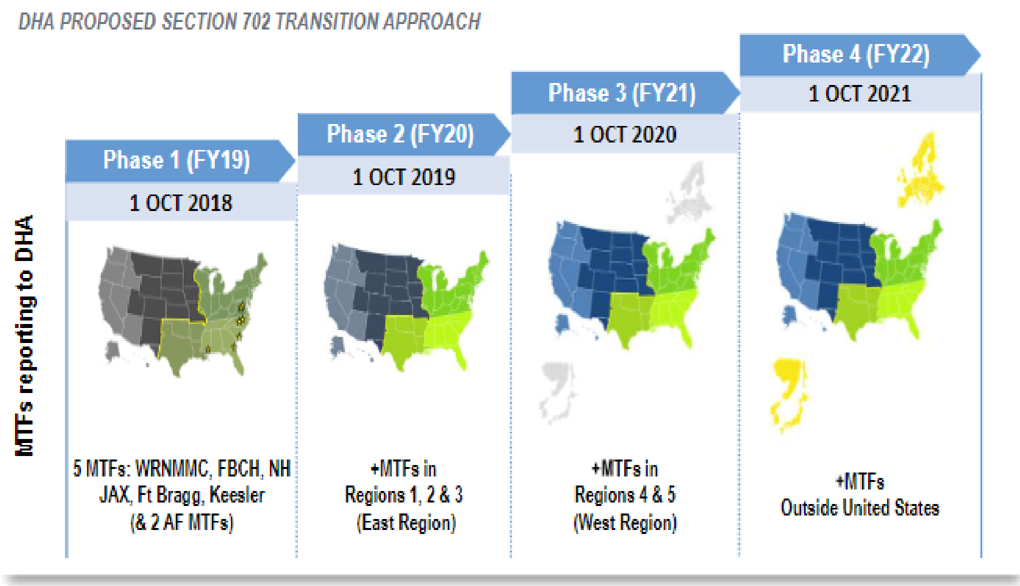
B. MEDICAL READINESS AND REQUIREMENTS MODEL

While the BA tells manpower planners how many personnel are funded in a given FY, manpower requirements are statements of the quantity and quality (i.e., skills, seniority) of people required to perform the work under consideration (Rodney, 2017). The Manpower requirements process is also the starting point in the National Defense Strategy (NDS), which provides a strategic requirement signal to the Navy (Rodney, 2017). As per Rodney (2017), the Manpower requirements process produces detailed sets of quantity with quality—the number of billets required for each Navy activity, specified by skills and seniority level.

Per Deputy Surgeon General Rear Admiral J. Terry Moulton's congressional testimony (*Ensuring Medical Readiness*, 2016), the modeling and projections for the required number of uniformed providers are based on the Operational Plans (OPLANS) and the Medical Manpower All Corps Requirements Estimator (MedMACRE). Admiral Moulton further notes that the OPLANS "outline the capabilities required to prosecute various wartime scenarios based on the Secretary of Defense's Defense Planning Guidance" (p. 3). The MedMACRE is a requirement tool that can run under different scenarios: for example, the most stressed OPLAN, Level IV (i.e., peacetime planning), will yield different requirements than if the MedMACRE were to run for OPLAN, Level III. Limitations of the modeling tool, however, include its underlying assumptions about how the NC practices SSP coding for operational planning: based on these assumptions, the model is unable to capture SSPs "masked" by an NC's most current billet or assignment. For example, NCs are selected to attend Graduate Medical Education (GME) after acquiring one or more SSPs. If GME is included in the MedMACRE simulation, the model will label GME candidates with only the name of their current subspecialty program and suffix T. This coding masks the SSPs previously held by the GME candidates.

C. POSSIBLE SOURCES OF SSP IMBALANCES IN THE NC

Spreadsheet data from CDR Ray shows an imbalance in operational and non-operational SSPs in the NC (H. Ray, email to author, November 13, 2018). According to an internally circulated Navy Medicine briefing card on MedMACRE phase II from July27, 2018, primarily, the imbalance in the NC's skill mix is due to a sweeping change in our National Defense Strategy, including increased focus on its "readiness." The 2018 National Defense Strategy focuses on rapidly adopting "Joint Forces," according to the Public Law 114-328 (Wilkie, 2018, p. 2). The National Defense Authorization Act (FY17 NDAA) focuses on the renewed emphasis on readiness and Joint Forces by restructuring organizational realignment at every level. FY17 NDAA mandates the uniformed force structure of the services' medical departments be based on readiness requirements and mandates the creation of a single agency, the Defense Health Agency (DHA). As part of the FY17 NDAA implementation process, the military treatment facilities (MTFs) are undergoing a restructuring in four phases, depicted in Figure 1 (Wilkie, 2018). The transition will take place in the mainland MTFs first, from the East to West Regions. Ultimately, all MTFs, including Outside Continental United States (OCONUS) or oversees MTFs, will report to the single agency, DHA, by the end of Phase 4, FY22 (September 30, 2022).



DoD MTFs transition to DHA in phases from Atlantic to Pacific and eventually OCONOUS.

Figure 1. DHA Proposed Transition Approach. Source: K. Hupfl (email to author, June 14, 2018).

The sweeping changes following the passage of FY17 NDAA and internal Department of Defense (DoD) health care reforms—i.e., the realignment of medical services under the DHA—serve as the catalysts for Navy Medicine to align its force structure more directly in support of the operational requirements set forth in the NDAA. The Navy Medicine briefing card from July 27, 2018, notes that the realignment of the uniformed force structure will, over time, increase the number of nurses in specialties required to support operational demands while decreasing specialties that have lower operational requirements Accordingly, Navy Medicine's force structure must meet the operational capability requirements of the U.S. Navy and U.S. Marine Corps operational needs. Navy Medicine's focus on the realignment of the operational commanders' mission objectives also increases in wartime inventories, because of the Navy and Marine Corps are moving towards the distributive operations per the FY17 NDAA directives. More important, operational readiness is paramount to combat survivals.

Another possible cause for SSP imbalances between the wartime SSPs and non-operational SSPs is availability of training ground. CDR Heather Ray, NC, BUMED expresses how the Navy beneficiaries' acuity levels are lower compare to the public (H. Ray, phone conversation, November 30, 2018). According to CDR Ray, this leaves limited space for the training needed to maintain the skills for desired SSPs.

This chapter has outlined a current change to the Navy Medicine's priority focus to realign with the National Defense Strategy (NDS) and CNO and CMC's operational demand. In turn, the supporting staff corps, like NC's focus has shifted to operational readiness. When it comes to NC wartime readiness, the organization's wartime SSP inventories suffers from understaffing. The next chapter reviews literature to determine what tool to use to address this issue of SSP understaffing.

III. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

This chapter offers a literature review that discusses the use of Markov Model in Manpower planning more broadly and examines previous work that applies Markov Model to address NC personnel issue, which informs this project's approach to providing solutions to the problem of suboptimal SSP distributions in the NC.

Various researchers like Bartholomew (1971), Smith (1970), Forbes (1971), and Vajda (1978) have all utilized probabilistic models in their research on manpower planning (Josiah, 2014). The probabilistic approach to manpower planning using Markov modeling was proposed by Bartholomew. Journals and theses are well supplied with articles that discuss implementation of Markov modelling in manpower planning. Sales (1971) validates Markov models use in Manpower with high reliability. Davies (1981) applies probability in the Manpower forecasting. Wijngaard (1983) articulates historical data aggregation in Manpower management science. Grinold and Marsall (1977) depict Manpower planning models by use of Markov. Jiang and Liu (2016) use hidden Markov models to forecast municipal waste (attrition) under uncertainty. Zanakis and Maret (1980) apply a Markov chain to Manpower planning. Ezugwu and Ologun (2017) use Markov Chain to build a predictive model for Manpower planning. Rowland and Sovereign (1969) give insights to internal Manpower supply analysis using Markov inside the industrial relation. Hall and Moore (1982) use Markov chain to forecast personnel under uncertainty related to recruiting shortfalls, stay or leave decision.

A. MARKOV AND THE NC

The use of Markov model in the military Manpower planning ranges across many communities and services. Two previous theses use Markov models to investigate accessions sources to optimize NC Manpower planning. These theses contribute to forecasting of next five years of force structure using different numbers of nurses from various sources of Accession; however, they do not address the imbalance issue in NC by the subspecialties (SSPs).

The first thesis, by Buni and Deen (2004), establishes the usefulness of the Markov model in NC Manpower planning. Like the present study, they use the model to investigate different accession sources for NC to forecast whether the force structure would meet targeted end strength over the next five years; however, their study focuses on personnel grades O1–O3.

Buni and Deen (2004) analyze data that the authors received from the Bureau of Medicine and Surgery (BUMED) Manpower Information System (BUMIS). The data covers FY1991 through FY2003; the authors use this data to predict future stock values for the ranks of O1 through O3. To make these predictions, Buni and Deen analyze a number of accession sources: The Navy Reserve Officers Training Corps (NROTC), the Medical Enlisted Commissioning Program (MECP), the Nurse Candidate Program (NCP), the Direct Accession (DA), the Baccalaureate Degree Completion Program (BDCP), the Health Services Collegiate Program (HSCP), and Full-Time Out-Service Training (FTOS). According to Harvie (2014), the accession source FTOST phased out in 1993; likewise, two other sources phased out in 1995, the BDCP and HSCP (Harvie, 2014).Buni and Deen use two groups of NC cohorts, FY90–94 and FY95–98, in their study. They follow cohort years 90–94 up to 10 years and measure the retention rate at different years of service marks—the four-, five-, seven-, and 10-year marks—to "allow [for] the [nurses'] completion of an initial obligation of four years and a follow-on assignment of three years" (p. 20). Buni and Deen follow the cohort of FY95-98 for five years. To analyze the data, they use a logistical regression model that includes the dependent variable of *stay* and independent variables of education level, gender, age, source of accession, and dummy variable for FY.

Buni and Deen find that 10-year retention pattern for the FY90-94 year cohort shows that accessions from the Recalls and the MECP consistently showed a higher, statistically significant probability of staying in the NC, while other accession sources showed lower probability of staying and were statistically insignificant (Buni & Deen, 2004, p. 70). They also find that being male had a positive significance for staying past their initial obligation compared to female at all years of decision point—at the four-, five-, seven-, and 10-year mark.

Buni and Deen's aim was to forecast the steady state of the NC using the Markov Model on the effect of the current accession sources. The following year, Kinstler and Johnson (2005) conducted research on the NC's challenge to determine the appropriate number of nurses to access for meeting the desired end strength authorized by congress. In their research, Kinstler and Johnson follow essentially the same methodology, but address assumptions made in Deen and Buni's study, in which all the accessions are assumed to be of Ensign Rank. The writers also include in their model the six subspecialties identified by Navy Medicine as vital to the mission.

In their model, the authors merge BUMIS data with Defense Manpower Data Center (DMDC) data to produce a combined database (CDB) and track nurse accession sources and career progressions for the years 1990 through 2001. They merge DMDC data into BUMIS to explore extensive demographic data. They also add a proxy variable for civilian unemployment rate from the Bureau of Labor Statistics (BLS). They then use a logistics regression like Buni and Deen to forecast the probability of nurse's promotion, stay in the Navy, or leave the Navy. They observe that the hiring sources (specifically the MECP) have a statistically significant effect on both retention and promotions; however, this delta is insignificant in the Markov Model (Kinstler, Johnson, Richter & Kocher, 2008, p. 625).

In contrast to these studies, which focus on the accession sources, the present study focuses on predicting the right mix of *quality*—accession numbers by operational force—to meet the necessary balance in the NC force structure for the wartime inventory planning within the congressionally authorized BA. This is important because the NC could influence the personnel flow at the accession source, which could reflect in the Markov Model.

The literature review shows that Markov application in the field of Manpower has wide use. Into the next section, a conceptual or the theoretical framework is established, which is employed in the next chapter.

B. CONCEPTUAL/THEORETICAL FRAMEWORK

To analyze whether current NC personnel planning aligns with the required end strength of the NC, this thesis creates a Markov model. The theoretical knowledge to create that model is derived from several scientific journals and books that support the application of Markov modeling to Manpower planning. The knowledge base of this thesis was provided by a book, *Statistical Technique for Manpower Planning*, by Bartholomew, Forbes, and McClean (1991) and by a journal article, "The Validity of the Markov Chain Model for a Class of the Civil Service," by P. Sales (1971). *Statistical Technique for Manpower Planning* catalogs many tools incorporated into the probabilistic models used by previous contributors to Manpower planning.

Bartholomew explains, "the object of manpower planning is matching the correct number of people with the appropriate skills to the jobs available at a given time to fulfill that organization's manpower needs" (1971, p. 3) According to Bartholomew, there are two considerations in manpower planning (p. 4): aggregates and uncertainty. Bartholomew et al. (1991) make two assumptions about the behavior of the Manpower system that enable the use of the probabilistic approach to these two concerns. The first is that "any manpower system can be examined through archival data" and that this data "aggregates to provide a useful description of the system" (p. 96). Second, these aggregates give insight into future uncertainties. Alternatively, the system could continue in a steady state. To address these inherently uncertain natures of the community in which the system operates, a Markov modelling is reliable for such a tool.

Vajda (1978) lays out the underlying theory in the Manpower modeling, arguing for the Markov model as the "main tool" for Manpower planning. Markov modelling's aid in the Manpower planning is further supported in the work by Bartholomew et al. (1991). Bartholomew et al. strongly suggest that Markov Chain Modelling answers questions about the ideal force structure for the military. The usefulness of the model in the military is because of the heterogeneity in the classification of the military personnel, such as rank, SSP, location, and years in service. Bartholomew et al. suggest using a transitional model based on the Markov Chain to deal with a heterogeneous system such as the Navy NC. The transitional matrix is discussed in the next chapter during the methodology and the implementation of the model.

Other works have established the forecasting ability of Markov models. As Sales (1971) notes, Young and Almond graphically validate; while Forbes validates by means of goodness of fit statistics. Sales conducts both validation techniques and both show minimum variance in validity either tested by the goodness of fit or the graph method. Guerry (2011) coins three types of flows in the modeling a Manpower system: (1) recruitment flows, (2) internal personnel flows, and (3) wastage. In the case of the NC, the internal personnel flows occur between the different personnel categories, such as a nurse’s SSP, rank and the assigned billets; and the wastage takes the form of attrition, leaving the service, or transition to communities other than the NC. The recruitment flows include the DA, Recalls, NCP, NROTCs or MECP; however, these recruitment flows are not modeled in this thesis, because no matter what the accession source, the NC can only be accessioned in the operational force categories just from the DA and the Recalls. The next chapter applies these tools to the problem of NC SSPs imbalances and Sales’ validation tools to show the model’s validity.

This chapter provides insight into the utilization of probabilistic approach to Manpower planning by the various researchers in various community and disciplines and establishes a theoretical or conceptual framework about the Markovian Models. To analyze whether current NC personnel planning aligns with the required end strength of the NC, this thesis uses a Markov model. The next chapter discusses data, provides model description and methodology of Markov Model creation from the raw data.

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IV. DATA, METHODOLOGY, MODEL VALIDATION AND IMPLEMENTATION OF MODEL, AND RESULT

Data for this thesis—including the raw data used for calculations in tables and figures—was obtained from a database of the Department of Defense Manpower Data Center (DMDC), on Rank, Accession Source, Fiscal Year, and Navy community, merged with data from the Bureau of Naval Personnel/Navy Personnel Command (BUPERS-NAVPERSCOM) personnel files on NCs' subspecialties (SSPs).

A. DATA DESCRIPTION

The data set contains annual snapshots on all Nurse Corps officers who were on active duty at the end of fiscal years 2010 to 2018. From the snapshot data, we produce pooled-cross-sectional data, with 3,097 observations. We calculate historical rates for accessions, promotion, continuation, and attrition using another analytical software and solutions tool, statistical analysis system (SAS), and exported as an Excel file. The variables included in the data are as follows:

1. Subspecialties (SSPs)

Per the NC Subspecialty Code Management Guidance, the subspecialty code (SSP) system is the personnel system used to manage the demand and supply of NC officers. The SSP system compares the nursing skill inventory to mission requirements (i.e., demand). This demand drives annual recruitment and training plans as well as the retention tools to maintain critical specialties. The SSP system allows for identifying NC officers with certain specialty experience, training, and education. This feature of experience level in turn helps executive officers determine for the NC Officer's assignment in a Military Treatment Facility (MTF) or operational theater.

SSP codes consist of a four-digit number and an alphabetic suffix: the number describes the subspecialty area, and the alphabetic suffix letter describes the level of experience, education, certification, and training (BUMIS, 2018). For example, the subspecialty "Critical Care Nursing" has a numeric code of 1960, and it can have any of the eight suffixes (BUMIS, 2018). This data set includes the suffixes S (one year of competency in the subspecialty), R (three years of competency), K (more than three years of competency plus passage of the board exam in the subspecialty), and P (master's degree in the subspecialty).

As per BUMIS (2018) the primary SSP or Subspecialty 1 should reflect a nurse's current, primary duty except for licensed independent practitioners (LIP) filling billets in the 1972, 1973, 1974, 1976, and 1981 specialties who are also pursuing career milestones (p. 3). "These individuals will maintain their LIP SSP" (BUMIS, 2018, p. 3) even though their primary role is as a department head (DH), officer in charge (OIC), senior nurse executives (SNE), executive officer (EX-O), or commanding officer (CO). All secondary and tertiary SSPs should describe last specialties or competencies held. The secondary or Subspecialty 2 is defined as "fully trained, might require a minimal refresher training to be fully credentialed" (BUMIS, 2018, p. 4; DoN, 2015, p. B-7). The tertiary or Subspecialty 3 is defined as "fully trained but might requires a lengthy refresher training to be fully credentialed" (BUMIS, 2018, p. 4; DoN 2015, p. B-7). At any given time, only three subspecialty codes can be maintained; which is consistent with the Medical Subspecialty codes per the OPNAVINST 1520.23 (DoN 2015, p. B-7). In addition to all the SSPs currently recognized in the SSP management guidelines, the data contain some obsolete codes—one 1980P and ten 1980Q—currently coded as 1981 (Nurse Midwife) according to Nurse Corps Personnel Planner CDR Ray (H. Ray, email to author, February 20, 2018). In addition to the SSP management guidelines regarding the use of the eight alphabetical suffixes, the data also has one extra suffix, T. According to CDR Ray, the new suffix T is to indicate that a nurse is in training.

2. Rank

The current NC rank for this thesis includes O-1 to O-6.

B. MARKOV MODEL

A Markov model is a probabilistic tool used to model randomly changing systems. Markov models are memoryless, which means that the probability that a system will occupy a given future state only depends on the current state—not on the past states. For this reason, the Markov model is suitable to forecast future states without contending anything about past policy or practices.

In this research, a Markov model is used to describe how NC officers, as (a cohort) move through a system (rank) to evaluate system behavior (growth, or steady states). Building the Markov models requires three basic assumptions.

The first assumption is that the system consists of finite states and that every entity of the system will reside in one, and only one, state (Bartholomew, 1971). A “state” is a category in which an element of the system may remain for a time-step (*t*).

Second, we assume the Markovian property, which holds that the probability that the system will transition to another state depends only upon its current state. In another words, that particular element’s entire history is really only dependent on where the element was in the previous time-step.

And finally, the third assumption states that the transition probabilities remain stationary, meaning “that the transition matrices for some manpower systems tends to remain constant over time or at least change only gradually from year to year” (Sales, 1971, p. 87).

Figure 2 depicts at an aggregate level the Markov model used in this thesis. In the model, the seven finite states are the NC ranks O1 through O6 and the absorbing state, attrite. As the figure shows, the second assumption holds true given that an NC only occupies one finite state at any time. For example, she cannot be both an Ensign (O1) and a Lieutenant (O3) at the same time. In the next time-step, if the NC was in state O1 during the previous time-step, then the NC can transition into one of three states: (a) remain as O1, shown by a curved arrow; (b) be promoted to the next grade or next state, O2, shown by the straight arrow pointing right; or (c) is no longer in the system (attrite).

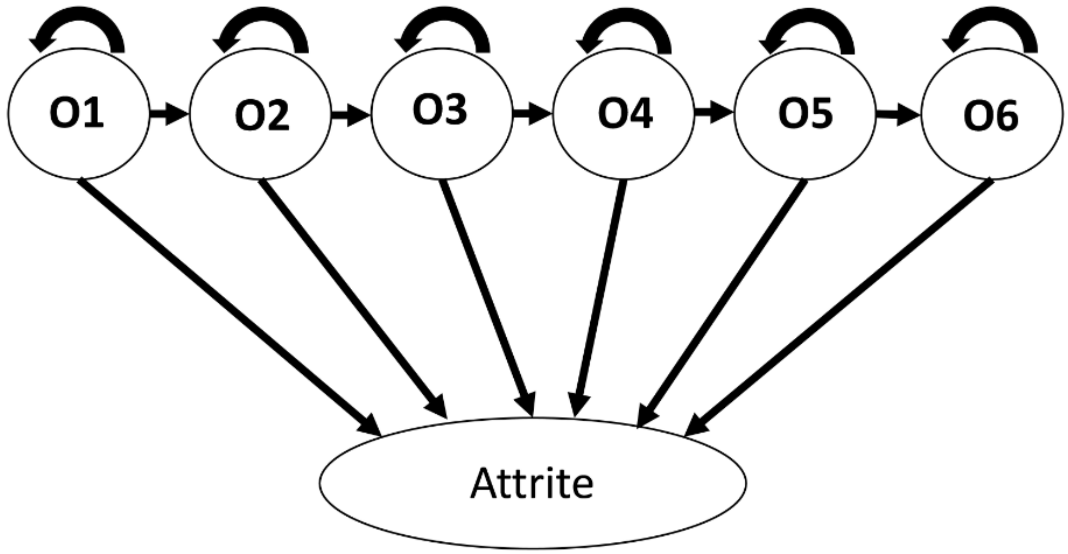

Figure 2. An Aggregate Level Markov Modeling Showing Two of the First Three Assumptions

C. METHODOLOGY

Like many other systems, the NC consists of a population of individuals who transition between states. For instance, an element might be in a state, n_i, at a given time *t*. At *(t+1)*, their state is n_j. Some elements remain at the same grade during that time step, while others might promote to the next grade. Still others leave the system during at that time. Elements that leave the system attrite.

An NC officer can only occupy one of six finite states that correspond to their paygrade. Based on the finite state assumptions, we create flow models that describe the behavior for each fiscal year in the DMDC data. From each flow model, we created a transition matrix, an example of which appears in Table 1.

Table 1. Sample of NC Transition Matrix

FY17	O1	O2	O3	O4	O5	O6	Att
O1	0.48	0.50	0.00	0.00	0.00	0.00	0.02
O2	0.00	0.52	0.45	0.00	0.00	0.00	0.03
O3	0.00	0.00	0.79	0.13	0.00	0.00	0.07
O4	0.00	0.00	0.00	0.82	0.10	0.00	0.07
O5	0.00	0.00	0.00	0.00	0.80	0.08	0.11
O6	0.00	0.00	0.00	0.00	0.00	0.88	0.12

This chapter has given a description of the data source, the Markov model in general, and the transition matrices built from the original data. The next chapter covers the validation and implementation of these transition matrices for an aggregate as well as subspecialty level of analysis and discusses some analytical limitations.

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V. NURSE CORPS MANPOWER DATA ANALYSIS USING MARKOV MODEL

The data we use for this analysis incorporates observations on every Navy NC officer on active duty at end of each fiscal year, from FY10 through FY18. We analyze (a) all NC officers who rank from Ensign (O1) to Captain (O6), and (b) include both operational and non-operational forces.

A. AGGREGATE LEVEL ANALYSIS

For an aggregate level analysis, our data only incorporates ranks from Ensign (O1) through Captains (O6) for FY10-FY18. The number of NC officers' distribution by its rank from Ensigns (O1) to Captains (O6) is shown in Figure 3. We lose four individuals who are all Flag-officers and were excluded from our analysis due to the small sample size.

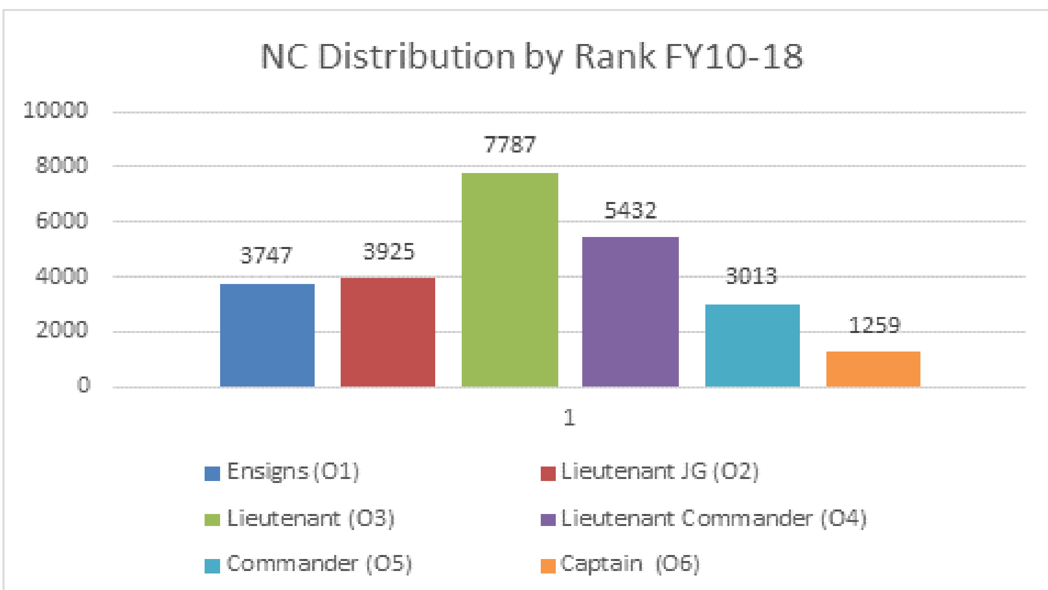


Figure 3. Number of NC Officers Distributed by Rank

1. Development and Validation

Prior to implementing the Markov model, we determine the stationary transition matrix, **P**, required to ensure the validity of our Markov modeling and forecasting. A large number of years in the data are used to create the transition matrix insure better estimates of the transition rates. However, the more years included in the estimates, it becomes more difficult to ensure that the transition rates are stationary. We consider this trade off when we build the transition matrix.

To determine the stationarity of the matrix, we build a confidence interval (CI) by calculating the standard error (*s.e.)* for each annual transition. Next we compare the aggregate transition rate for that particular transition to determine if it is contained within the CI. The more CIs that contain the respective aggregate transition rates, the more stationary the model. According to Sales (1971), the estimated standard error *(s. e.)* obtained by using the binomial distribution.

$$s.e.(p_{ij}) = \sqrt{\frac{p_{ij}(1-p_{ij})}{n_i}}, \qquad (1)$$

where p_{ij} is the true underlying transition probability from i to j and where n_i is the number of elements that started the time-steps in state i.

When we first built the transition matrix, **P**, using all eight years of aggregate data, only 30% of the transition rates were sufficiently stationary, which, according to Sales' goodness of fit test, is insufficient to call the transition matrix valid. Thus, we took a remedial action in building the **P** by shrinking the window of empirical data, from older years first until after seven remedial actions, a transition matrix that validated at 73% was determined using empirical data for FY 2016 and 2017, shown in Table 2.

Table 2. Validated Transition Matrices, **P**

FY16-17	O1	O2	O3	O4	O5	O6	Att
O1	0.46	0.51	0.00	0.00	0.00	0.00	0.03
O2	0.00	0.50	0.47	0.00	0.00	0.00	0.03
O3	0.00	0.00	0.81	0.11	0.00	0.00	0.08
O4	0.00	0.00	0.00	0.83	0.09	0.00	0.08
O5	0.00	0.00	0.00	0.00	0.81	0.08	0.11
O6	0.00	0.00	0.00	0.00	0.00	0.83	0.17

2. Fixed Inventory Analysis

Having determined the transition matrix, the next step is to implement the model using the Bartholomew's equation of Manpower Inventory Models given by

$$\mathbf{n}(t) = \mathbf{n}(t\text{-}1) * \mathbf{P} + R * \mathbf{r} \tag{2}$$

where,

- $\mathbf{n}(t)$ are the expected number of individuals in a given state (say, a rank) at that time-step (for this study, a time-step would be measured in a full FY);
- $\mathbf{n}(t\text{-}1)$ is the inventory vector at the previous time step;
- $\mathbf{n}(0)$ represents the initial inventory vector;
- **P** is a transition matrix;
- R is a scaler that describes the number of new accessions; and
- **r** is a vector describing how the cohort is distributed among each states, between 0 and 1.

To implement equation (2), we calculate the vector, **r**, from the empirical data, FY2011 through 2018, provided in Table 3. Where, **r**=[0.93, 0.05, 0.02, 0.00,0.00,0.00] just as our data, then 93% of new personnel recruited will enter category one (O1), 5% will enter category two (O2), 2% will enter the categories three, (O3) and the cohort have a 0% probability of being recruited at the rank of O4, O5 or O6 (categories five and six).

Table 3. Calculated Vector, **r**

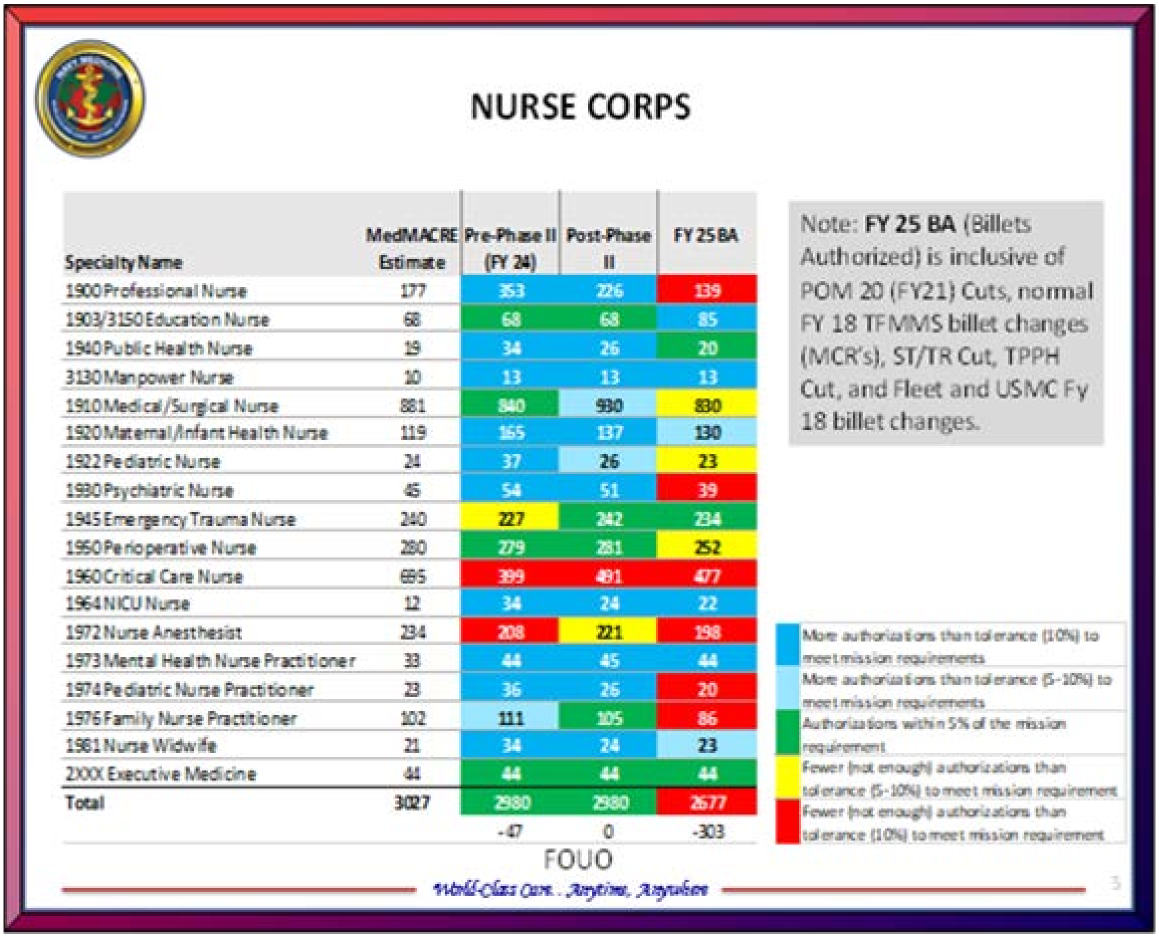
r					
O1	O2	O3	O4	O5	O6
0.93	0.05	0.02	0	0	0

Table 4 provides the results of the implementation of Bartholomew's inventory equation, equation (2). We use beginning inventory, $\mathbf{n}(0)$, for FY19 from the DMDC data and listed by rank, O1 through O6. We then solve for the decision variables, annual accession numbers, to forecast annual E/S for the planning period FY20–25 using the Markov chain. The values of these decision variables are calculated based on the limitations expressed in the constraints. The constraints we apply to the formula implementations are as follows: (1) the ratio of *R1/R2*±.1, signifying that an allowable increase or decrease in number of accessions is equal to ± 10%; and (2) each year the accession goal is greater than or equal to (≥) 160 NC. This number is an estimate of accession number per year after restructuring under DHA, based on the DMDC and BUMIS record.

Table 4. Implemented Bartholomew Inventory Equation Using **P**

		O1	O2	O3	O4	O5	O6	Total	Target	R1/R2±.1	R
	n()										
FY19	0	355	463	999	607	327	138	2889			
FY20	1	376	426	1025	615	318	141	2901	2991		229
FY21	2	366	417	1029	624	311	142	2890	2928	1.1	208
FY22	3	344	407	1027	632	306	143	2860	2865	1.1	189
FY23	4	318	390	1021	639	303	143	2814	2802	1.1	172
FY24	5	295	367	1008	644	301	143	2757	2739	1.073796	160
FY25	6	285	344	986	646	300	142	2703	2677	1	160

Under the given constraints applied, we get our accession result or solution under the far right or the column R of the Table 4 and total inventory by rank and each proceeding FY is provided by the corresponding coordinates. An (**n**) represents the proceeding FY. For example, **n**(*0*) provides a beginning inventory for FY2019, this data is obtained from CDR Heather Ray, a Nurse Corps Personnel Planner at BUMED (H. Ray, email to author, November 13, 2018). For FY2020, **n**(*1*) through FY2025, **n**(*6*) are the calculated results indicating inventories by rank and totals per FY. The target is again an educated guess and we use our Benchmark FY25, per Ray, one of the Senior Nurse Corps Manpower Practitioners our known BA is only for FY25, while undergoing the all services realignment under the DHA (H. Ray, email to author, November 13, 2018). Figure 4 shows that known benchmark BA for FY25.

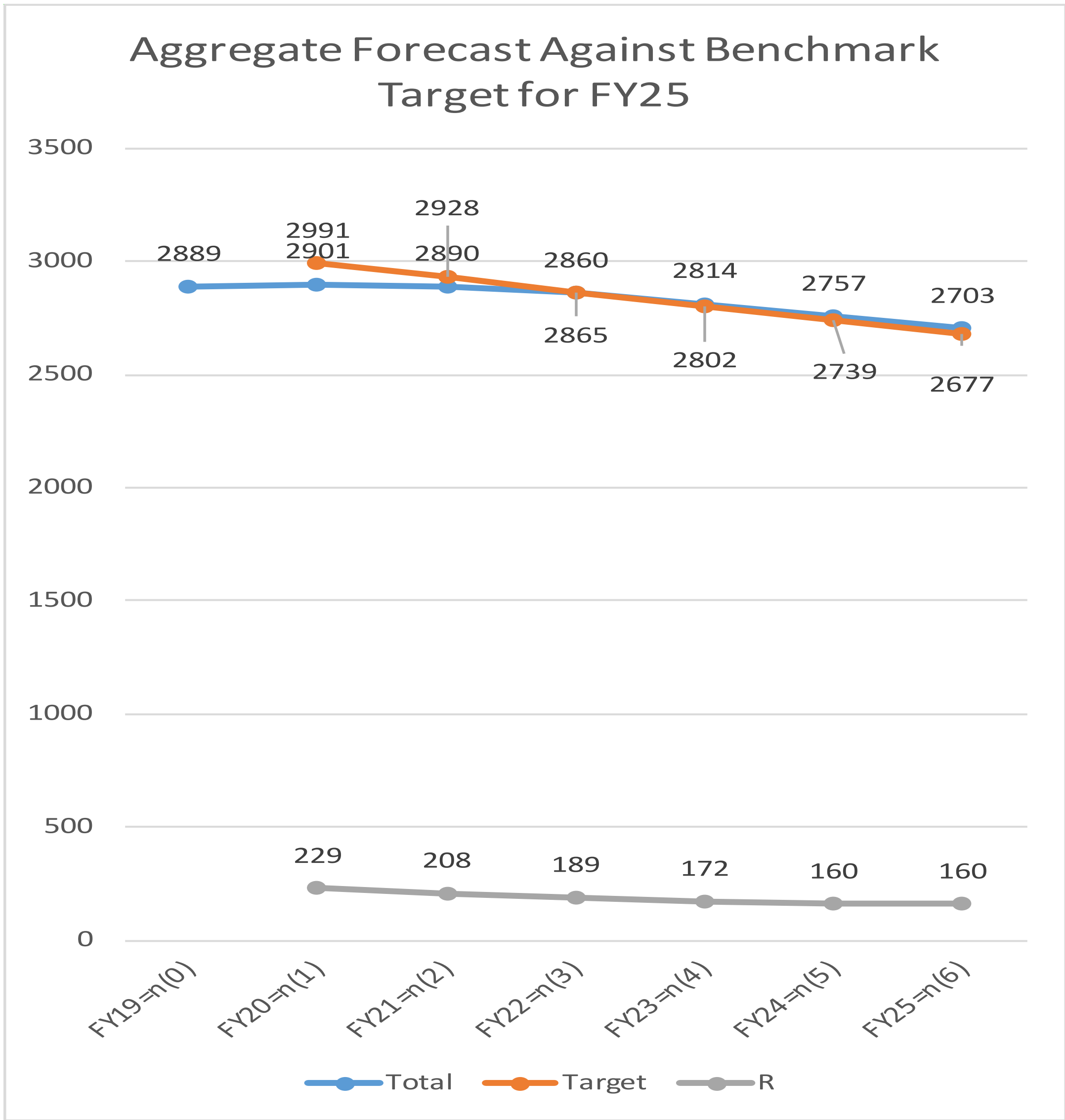


Specialty Name	MedMACRE Estimate	Pre-Phase II (FY 24)	Post-Phase II	FY 25 BA
1900 Professional Nurse	177	353	226	139
1903/3150 Education Nurse	68	68	68	85
1940 Public Health Nurse	19	34	26	20
3130 Manpower Nurse	10	13	13	13
1910 Medical/Surgical Nurse	881	840	930	830
1920 Maternal/Infant Health Nurse	119	165	137	130
1922 Pediatric Nurse	24	37	26	23
1930 Psychiatric Nurse	45	54	51	39
1945 Emergency Trauma Nurse	240	227	242	234
1950 Perioperative Nurse	280	279	281	252
1960 Critical Care Nurse	695	399	491	477
1964 NICU Nurse	12	34	24	22
1972 Nurse Anesthesist	234	208	221	198
1973 Mental Health Nurse Practitioner	33	44	45	44
1974 Pediatric Nurse Practitioner	23	36	26	20
1976 Family Nurse Practitioner	102	111	105	86
1981 Nurse Midwife	21	34	24	23
2XXX Executive Medicine	44	44	44	44
Total	3027	2980	2980	2677
		-47	0	-303

Figure 4. Benchmark FY25 BA, as per MedMACRE. Source: H. Ray (email to author, November 13, 2018).

We can incorporate an ever-changing nature of real world into this model easily because the model is very flexible and can adjust to the most current policy information. For example, the target goals can adjust to known accurate numbers or to policy that seeks a certain number of accessions each year and/or the maximum and minimum allowable tolerance level change. After each adjustment, the optimization Solver rerun to forecast the new decision variables. In the Figure 5, the orange line shows total target and the blue line shows how the model is predicting. Moreover, our model predicts very close to the target for FY22–24; underpredicts for FY20 and 21 compare to our target goals; and overpredicts for until FY25. One of the reasons could be because of our constraints application and could be from how we had manipulated our annual goal to be at least 160 NC. To overcome this initial underproduction, we could relax on one or both the constraints we had applied.

In the bottom of Figure 5, the gray line shows an accession number increases from year to year.



R (≥) 160, *R1/R2* ±10%

Figure 5. Forecasted Inventories against the Estimated Targets

The application of transition matrix **P** in the Bartholomew equation therefore can provide solutions to a problem like what accession mission must be over the next six years to achieve a given E/S, for example, the benchmark for FY2025 that we discuss the implemented into our solver.

3. Steady State Analysis

In addition to the implementation of the Bartholomew's inventory equation to forecast a future inventory or accessions goals, a fundamental matrix **S** can also easily be constructed using the following equation:

$$\mathbf{S} = (\mathbf{I} - \mathbf{P})^{-1}\,. \tag{3}$$

The implementation of the fundamental matrix, equation (3), yields the following in Table 5.

Table 5. A Fundamental Matrix, **S** Constructed from Our **P**

S	O1	O2	O3	O4	O5	O6
O1	**1.85**	1.91	4.58	3.00	1.37	0.64
O2	0.00	**2.01**	4.82	3.15	1.44	0.68
O3	0.00	0.00	**5.16**	3.38	1.55	0.72
O4	0.00	0.00	0.00	**5.92**	2.71	1.27
O5	0.00	0.00	0.00	0.00	**5.29**	2.48
O6	0.00	0.00	0.00	0.00	0.00	**6.04**

This estimated fundamental matrix **S** provides useful information about a particular nurse corps expected length of time spent in one rank before advancing to the higher rank, provided the nurses have not experienced an attrition. Starting in the cell (O1, O1) at the top left corner cell and proceeding down the diagonals to the bottom right (O6, O6) shows an expected length of time any particular nurse remains in the particular rank if she ever made it to that rank. For example, a NC's expected length of time to remain in rank of O2 is roughly two years represented by the coordinate of (O2, O2), or five years and two months in the rank of O3 as denoted in coordination of (O3, O3) given they ever made it to the respective ranks.

a. What to Make of the Off-diagonals

By an algebraic calculation we can calculate conditional probabilities, from our model in Table 8, for example, what is the probabilities of a NC ever making it to the rank of Captain (O6) provided she started at the rank of Lieutenant (O3) is given by 0.64/4.58=0.14. It means a nurse who commissioned as an O3 has roughly a 14 % chance of ever making it to the rank of O6. Mathematically, this conditional probability is given as pr. (individual **makes** it to j state | started in i) **or** S_{ij} / S_{jj}.

b. Estimating Steady State Inventory

The latest model we build, the Fundamental Matrix **S**, provides a long-term steady state inventory calculation. Mathematically, this steady state inventory is denoted by n* and is given by an equation **n*=*R*rS**.

Given our system is a steady state, from one time-step to another time-step variance is at minimum level we use the steady state equation to calculate the steady-state inventory. If NC system is a steady state that has very little fluctuation in its behavior producing high validity of CI then the application of this long-term steady-state inventory calculation yields that we are required to accession 202 NC officers each year for a known BA of 2677 in FY2025.

The steady state inventory calculation in Table 6 yields solution (202NC) per year. And the average of the accession number given by the Fixed Inventory Analysis, i.e., about (186 NC) each year.

Table 6. Steady State Inventory Calculation by Implementing the Steady State Equation

n*=RrS							
r							
O1	**O2**	**O3**	**O4**	**O5**	**O6**		
0.93	0.05	0.02	0	0	0		
348	379	930	608	279	131	**2675**	**202**
FY25 goal	= 2677						

This close estimation of the accession goal either using Fixed Inventory or the long-term steady-state means the expected behavior of the NC system is stable and ensures that our model can be utilized for other NC characteristics. Next, we model the NC operational force versus the non-operational force, incorporating Ensigns through Captains.

B. SUBSPECIALTY ANALYSIS

For a subspecialty-level analysis, our data incorporates the operational and nonoperational status, in addition to the grades or ranks from Ensign (O1) through Captains (O6) for FY10–18 that we analyzed at the aggregate level of analysis. A summary of the data is providing in Figure 6.

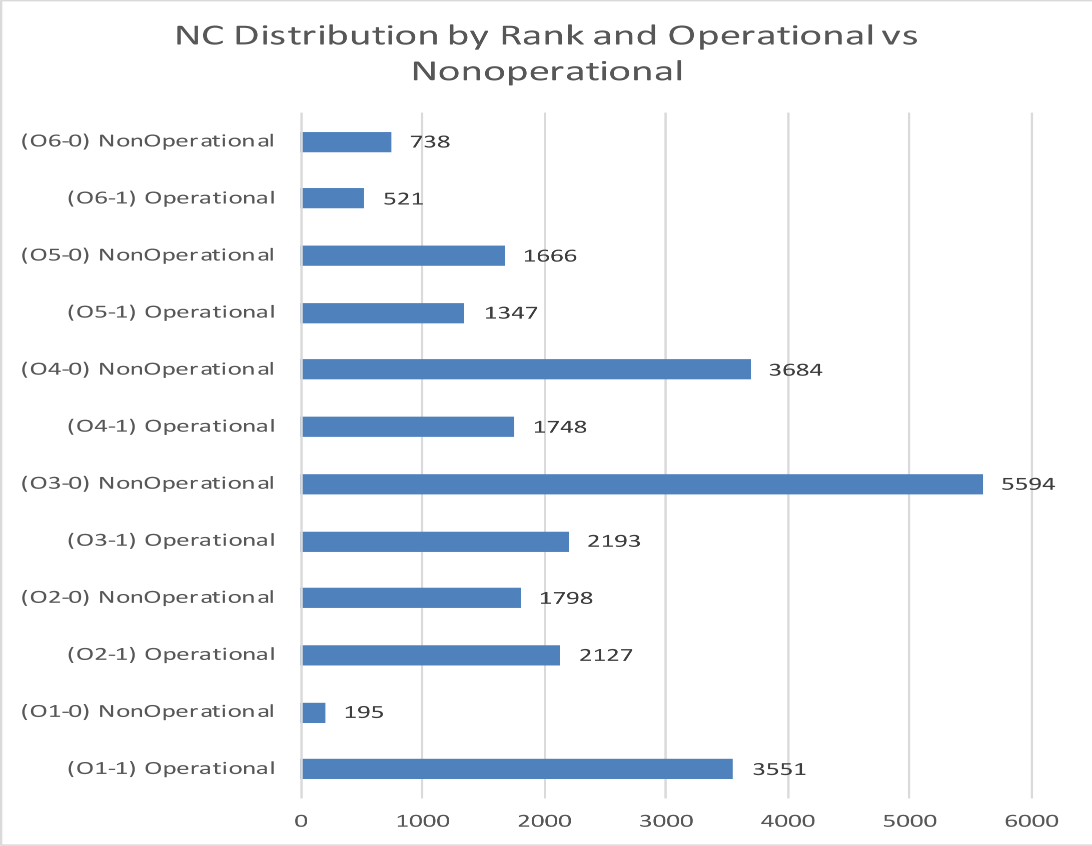


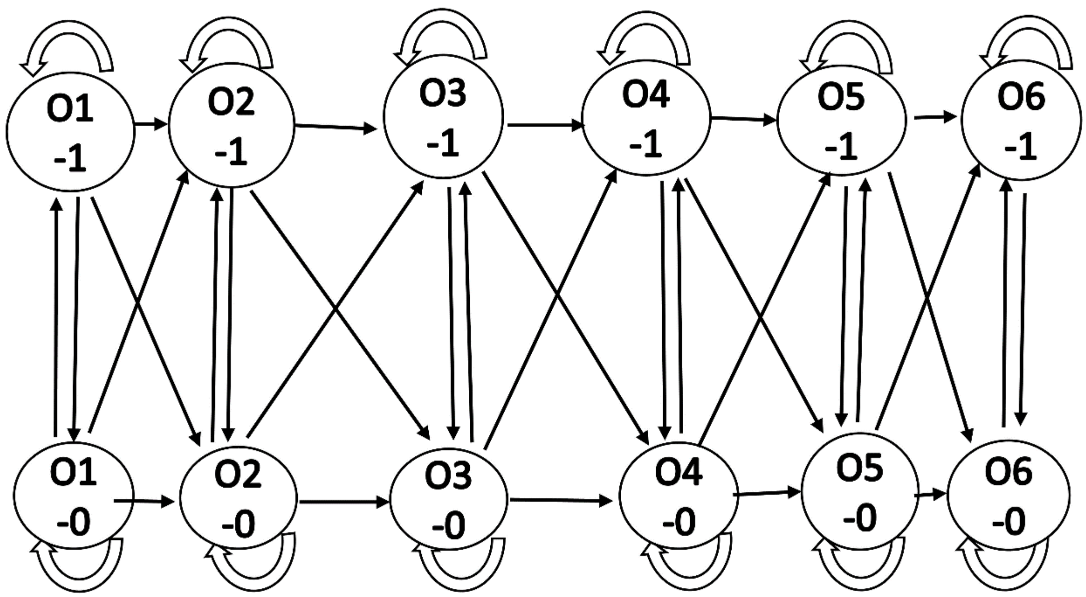
Figure 6. Navy NC Officers Operational and Non-operational Force Distribution by Rank

Using this data information we build a new transition matrix, $\mathbf{P}_{ssp}$. The new $\mathbf{P}_{\mathbf{ssp}}$ is utilized to address this thesis objectives of meeting the right number and right type [or right specialties, either operational or non-operational] of nurses in any given FY.

1. Development and Validation: P_{ssp}

The aggregate level analysis provides a useful description of the NC systems' behavior. Next, to address this thesis's objective—determining the right number and right type (i.e., right specialties, either operational or non-operational) of nurses in any given FY—we build a new transition matrix, $\mathbf{P}_{\mathbf{ssp}}$. To build this matrix, we use NC data from the DMDC from FY10 through FY18 that encompasses subspecialty (SSP) as well as grades (ranks).

In building the $\mathbf{P}_{\mathbf{ssp}}$**,** we make four assumptions: First, as Chapter I explains, and as in Kinstler and Johnson (2005), "six subspecialties (SSPs) were identified by the literature as being 'critical' to the Nurse Corps during times of increased operational commitments" (p. 20). Second, as per OPNAVINST 1520.23, Part B, only three subspecialties can maintain in the officer's record (DoN, 2015). In the model, to be considered "operational," an NC must have at least one of the six critical subspecialties. Thus, all three subspecialties were included in the modeling. Third, to avoid the incompetence liability during the medical deployment time, a minimum of one year of competency is required for an NC to count toward full operational readiness. For instance, NCs with an alphabet suffix of T (training), E (less than one-year experience in that field), or V (just having completed the accredited vocational studies) are excluded from consideration as a fully operationally ready. Lastly, to ensure we have enough of a sample to effectively estimate some of the smaller states, we use four years of data in building the $\mathbf{P}_{ssp}$**.** We take this chance, despite the fact that Sale's method described above only finds that 44% of transitions are sufficiently stationary. Using these assumptions, we build a new transition matrix, $\mathbf{P}_{ssp}$, to capture subspecialty transition probabilities within the NC's operational and non-operational forces. Figure 7 provides a graphical representation of these transitional probabilities.



Arrows represent probabilities of moving to a different state, while arcs represent remaining in the same state. Additionally, from each node, there is a chance of attrition.

Figure 7. Graphical Representation of $\mathbf{P}_{ssp}$ Model

The transition matrix $\mathbf{P}_{ssp}$, which gives the probability of these transitions, is shown Table 7.

Table 7. Subspecialty Transition Matrix, $\mathbf{P}_{ssp}$

				Aggregate Probs FY14-FY17										
P		**O1 0**	**O1 1**	**O2 0**	**O2 1**	**O3 0**	**O3 1**	**O4 0**	**O4 1**	**O5 0**	**O5 1**	**O6 0**	**O6 1**	**Attrition**
O1	**0**	0.478	0.015	0.316	0.144	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.047
O1	**1**	0.000	0.086	0.672	0.172	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.069
O2	**0**	0.000	0.000	0.388	0.202	0.267	0.096	0.000	0.000	0.000	0.000	0.000	0.000	0.048
O2	**1**	0.000	0.000	0.001	0.399	0.035	0.535	0.000	0.000	0.000	0.000	0.000	0.000	0.030
O3	**0**	0.000	0.000	0.000	0.000	0.627	0.205	0.075	0.010	0.000	0.000	0.000	0.000	0.084
O3	**1**	0.000	0.000	0.000	0.000	0.039	0.767	0.004	0.100	0.000	0.000	0.000	0.000	0.091
O4	**0**	0.000	0.000	0.000	0.000	0.000	0.000	0.771	0.069	0.090	0.001	0.000	0.000	0.069
O4	**1**	0.000	0.000	0.000	0.000	0.000	0.000	0.039	0.819	0.053	0.010	0.000	0.000	0.079
O5	**0**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.811	0.036	0.051	0.000	0.102
O5	**1**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.816	0.028	0.037	0.094
O6	**0**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.805	0.026	0.169
O6	**1**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.841	0.154

In this Table, 1 & 0 represents an operational and non-operational NC, respectively, and O1 through O6 are the NC ranks from Ensign to Captain. For example, if the NC is in state O1-0, then the NC officer is non-operational, while, if she is in O1-1, then she is operational. Similarly, if the NC promoted from O1-0 to O2-0, then her operational status did not change; however, if she promoted from O1-0 to O2-1, then her operational status and her rank both changed. On the other hand, if the NC started as O1-0 but was not promoted and did not change her operational status during that time-step, then the coordinates (O1-0, O1-0) give her probability of remaining in the same state. One of the considerations we made while conducting this validity test was to exclude any transition with a probability of 0.005 or less because of its minuscule chances of occurring. Therefore, we excluded the following three transitions, highlighted in red in Table 8.

In order to utilize this new $\mathbf{P}_{ssp}$, we obtain a new vector, $\mathbf{r_{ssp}}$ (Table 8) from historical-accession distribution probabilities from FY10–18, obtained from DMDC. This new $\mathbf{r_{ssp}}$ encompasses rank and both operational and non-operational SSPs across all accessions.

Table 8. $\mathbf{r_{ssp}}$, Historical Accession Probabilities by Rank and SSPs

rssp											
O1 0	O1 1	O2 0	O2 1	O3 0	O3 1	O4 0	O4 1	O5 0	O5 1	O6 0	O6 1
0.881	0.046	0.024	0.030	0.010	0.006	0.001	0.002	0.000	0.000	0.000	0.000

To maximize the verisimilitude of the subspecialty transition model, $\mathbf{P}_{ssp}$, four sets of information are defined and determined: initial NC inventory, total target E/S, estimated proportion of operational vs. non-operational E/S, and accession goals. First, in order to project five to six years down the line, a current an initial inventory $\mathbf{n}(0)$ for each rank and operational as well as non-operational NCs are determined using the NC information obtained from the Nurse Corps Personnel Planner, CDR Ray. Table 9, created from the spreadsheet obtained from CDR Ray, displays this data (H. Ray, email to author, November 13, 2018).

Table 9. Current Beginning Inventory of NC FY19 Showing Operational and Non-operational by its Rank. H. Ray (email to author, November 13, 2018).

	CAPT	CDR	LCDR	LT	LTJG	ENS	Total	%
Operation	18	101	221	515	267	140	1262	0.44
Non-oper.	118	225	384	491	186	210	1614	0.56
	CAPT	CDR	LCDR	LT	LTJG	ENS	2876	

Second, a goal for a target end strength (E/S) is scaled down linearly from current target goals to the known benchmark for FY25 of 2667 and established based on data obtained from CDR Ray on November 13, 2018; this goal is shown in Figure 8.

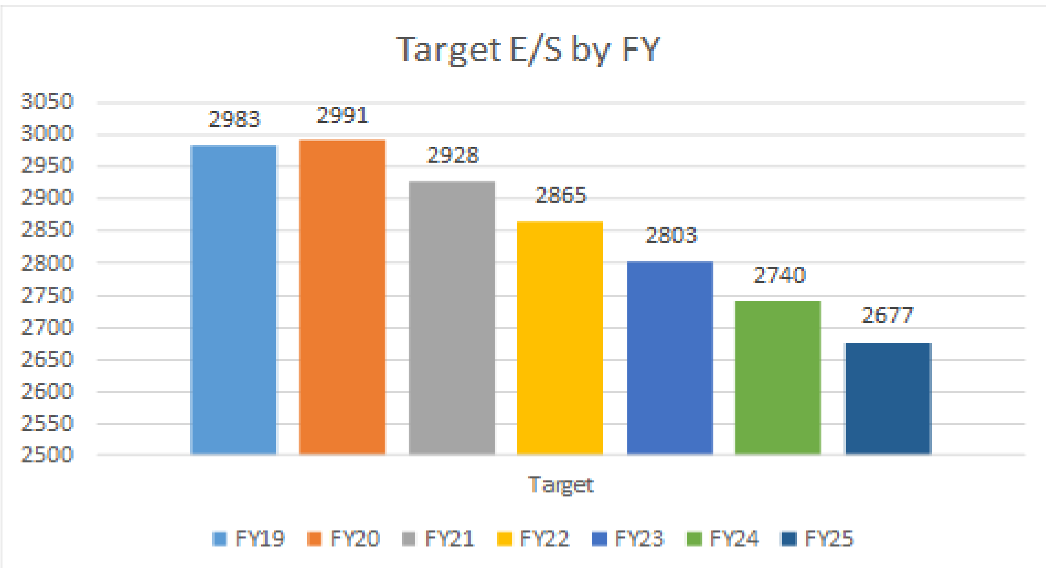


Figure 8. Total Targeted (Assumed) E/S by FY. Adapted from H. Ray (email to author, March 10, 2019).

Third, because the NC does not manage its personnel by operational and non-operational E/S, projected quantities of operational and non-operational E/S are calculated based on the assumed E/S in Figure 8 and operational and non-operational force distribution in Table 9; these quantities are shown in Figure 9. Considering that, all else being equal, the targeted operational forces E/S will continue to make up of about 44% of the total NC forces, a new targeted operational force is calculated, shown in Figure 9.

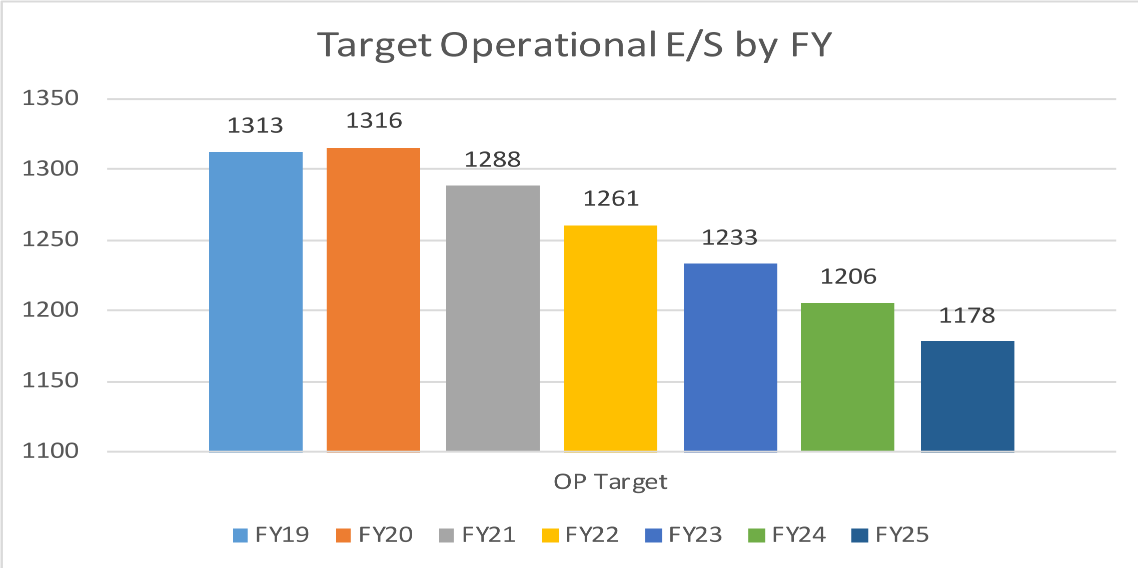


Figure 9. Assumed Targeted Operational E/S

Lastly, we establish the minimum accession goals per year at 140 and the tolerable increase or the decrease accession rate from the (*t*-1) is at 10%.

2. Fixed Inventory Analysis Result: SSP

After implementing the Markov Inventory Model equation, we made use of all four sets of information-defined constraints to get an optimization of objectives variables, *R*. To optimize the desired variables, we minimized the squared deviations for force totals from the targets. We obtained the result shown in Figure 10. The top section of this figure provides the target E/S, shown by the line in yellow, and the predicted total NC force for each FY given the targeted E/S, shown by the line in blue. The middle section of the figure provides a total predicted NC force for each FY: operational, given by the orange line, and non-operational (i.e., shore) given by the gray line graph measured against the assumed targeted operational E/S as defined by the bold blue line. Per our modeling the targeted operational force shown by the bold blue line is under the line orange every year starting FY21. This means our target for the operational force is undershooting. In our defined scenario we keep operational force at constant proportion from year to year, i.e., we keep our operational force proportion to be at 44% only. The bottom graph of Figure 10 shows predicted accession goals for FY20–25.

Figure 10. Accessioned and Operational Forecasts Using BUMIS Initial Inventory at the Beginning of FY19.*R1/R2* (±).1 & *R* ≥140

Figure 11 provides a breakdown of total operational and nonoperational forces. In the columns, O1 through O6 represent NC Ranks, while the suffixes 0 and 1 mean respectively non-operational and operational.

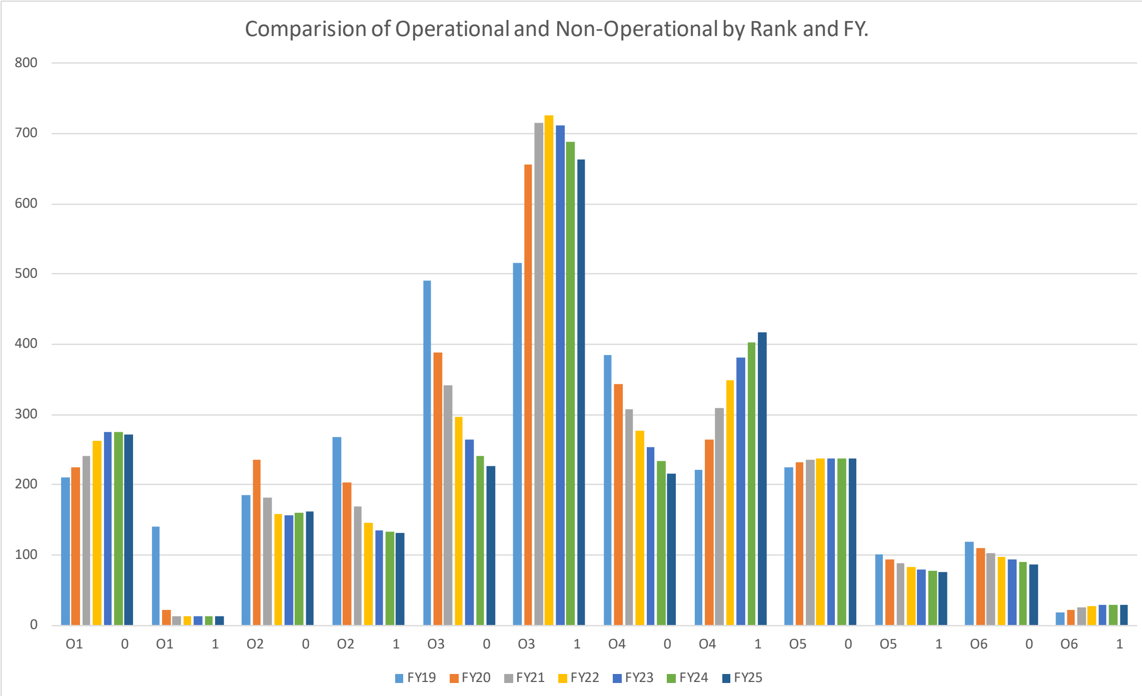


Figure 11. Breakdown of Operational (1) and Non-operational (0) by Rank and FY

As the table shows, consistently for each FY the distribution of the operational and non-operational forces demonstrates the following behavior: (1) most of the forces in ranks O1, O5, & O6 possess non-operational SSPs. On the other hand, (2) the majority of the forces in ranks O3 & O4 possess operational SSPs. Finally, (3) the rank of O2 has an almost equal number of operational and non-operational forces.

3. Steady State Analysis: SSP

Like the aggregate level analysis, we built a fundamental matrix, **Sssp**, by constructing an identity matrix, **Issp**, then taking an inverse of the difference (**Issp – Pssp**) to get **Sssp.** We used **Sssp** to forecast steady-state inventory for SSPs. As was discussed earlier, the steady-state inventory is given by $\mathbf{n}^* = R\mathbf{r}\mathbf{S}$.

Per Kinstler and Johnson (2005), on average, the NC accesses 250 NCs/year. We used this information and our $\mathbf{r}_{ssp}$ and **Sssp** to calculate our steady-state inventory. Figure 12 provides the result.

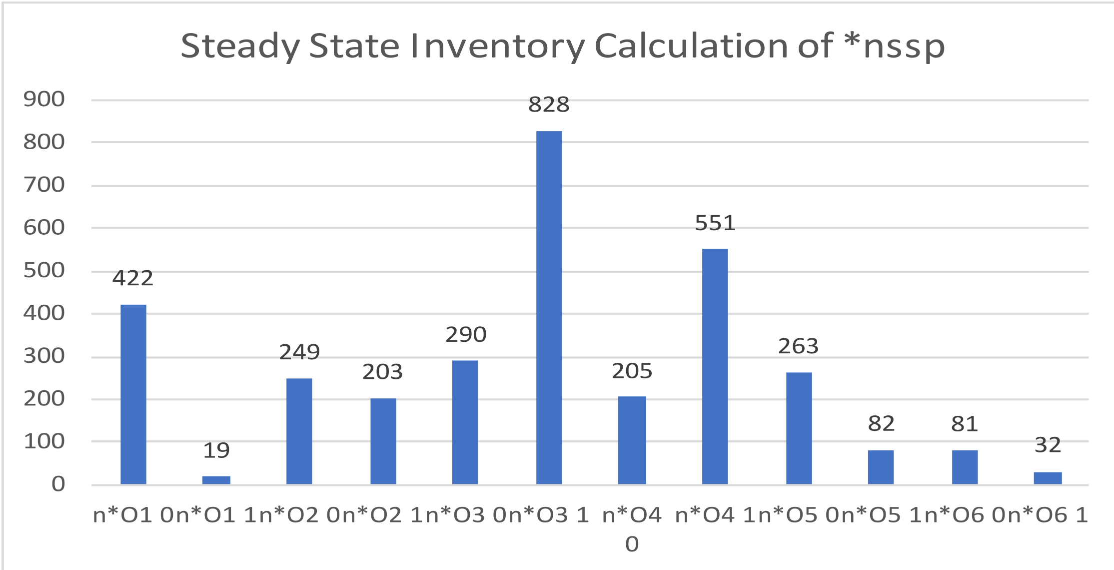


Figure 12. Solutions Showing Steady State Inventory Analysis, $\mathbf{n}_{ssp}$*

These results assume that the personnel flow in a system like the NC organization reaches its steady state. In addition, all else being equal—i.e., (1) the accession rate ($\mathbf{r}_{ssp}$) remains steady as we have calculated; (2) we use a hypothetical number of accessions is R=250; and (3) the transition matrix, $\mathbf{P}_{ssp}$, is in a steady-state—then the resulting force structure is given in figure 12. Like our solution for the fixed inventory analysis, the steady-state analysis also produces a similar behavior. i.e., the ranks of O1, O5, and O6 possess forces made up of more non-operational. On the other hand, the ranks of O3 and O4 possess forces more operational. Finally, the rank of O2 has almost equal number of operational and non-operational forces.

This finding is critical in terms of our modeling strengths. This ability to provide an almost identical behavior either by the fixed inventory [$\mathbf{n}$ (t) $=\mathbf{n}$ $(t\text{-}1)$ $*\mathbf{P}$ + R*$\mathbf{r}$] or the steady-state [$\mathbf{n}$*= R**rS**] means we build a reliable model, because the system doesn't need to fight off in order to meet the drastic changes in the policy or requirements. In other words, the model can adapt to drastic changes but still predicts a reliable forecasting solution. Even, in simpler terms, our model's forecasting ability is valid, because the transition probabilities are either constant or changes gradually. Either the constant or the gradual changes depicted by our model make a convincing case for one of the most difficult assumptions we made in describing to build a Markov model in Chapter IV. From the three assumptions usually made in building for the Markov models, the last assumption, i.e. to reach that steady state is often most difficult to achieve. What does it mean to accomplish that steady state in terms of the manpower planning? This means that our model provides a reliable forecasting tools in order to study the future NC system's behavior.

C. LIMITATIONS

To accomplish a sound and reliable "goodness of fit tests" by Sales (1971) we sacrificed our sample size and only utilized total of two fiscal years (FY16 and FY17) that yielded our aggregate level of stationarity at 73%. We used transition matrix **P** build from this small size sample to study about expected behavior of the NC system. On the other hand, we took our chances by taking larger sample of four years to build our transition matrix for Subspecialty, $\mathbf{P}_{ssp.}$ We took this chance to capture enough samples for some smaller unit subspecialties (SSP). Upon goodness fit test, the $\mathbf{P}_{ssp}$ only yielded 44% of CI.

Our model forecasts the needed number of NC accession without regards to where or what the accession source might have been. Similarly, the predicted operational forecast incorporates any of the six operational subspecialties at any specific ranks.

D. SUMMARY

This chapter provides an analytical discussion at both the aggregate and subspecialty levels. The models of both the aggregate level and subspecialty level behave tolerably well. The next chapter concludes with discussions about the Markov model's strength in manpower planning, a summary of our analytical work and recommendations based on our modeling, and lastly provides a roadmap for future research.

VI. CONCLUSION AND RECOMMENDATIONS

This chapter completes the study, first by summarizing the findings and discussing strengths and limitations of Markov modelling in the context of the NC system, then by offering recommendations for future research.

A. SUMMARY OF FINDINGS: STRENGTHS AND WEAKNESSES OF USING MARKOV MODELING IN NC MANPOWER SYSTEMS

Our objective in this thesis is to build a more precise way to optimize NC surge force planning and to forecast a balanced mix of operational critical wartime inventory and non-operational forces for the Navy NC. Markov models are an established tool in manpower management because they can be used not only to predict the aggregate behavior of the system but also to model various categories of the system, e.g., paygrades, years in service, cohorts, and job specialties. Other writers, including Ezugwu and Ologun (2017), make a similar confidence claim regarding the Markovian models' uses in manpower management applications. Ezugwu and Ologun note that "with respect to organizational management, numerous previous studies have applied Markov chain models in describing title or level promotions, demotions, recruitments, withdrawals, or changes of different career development paths to confirm the actual manpower needs of an organization or predict the future manpower needs" (p. 557).

That said, the weakness of using Markov models in the context of the NC specifically rests on the NC community itself: it is a very small community with diverse sub-specialties. For example, as per Navy Nurse Corps Subspecialty Code Management Guidance, the Nurse Corps codes its subspecialties under 19 categories (BUMIS, 2018). Therefore, the small number of NC personnel stretch across those 19 categories thinly, making the system difficult to model because some smaller sub-communities' transitional probabilities become unreliable for building a subspecialty-specific transition model. We therefore decided the most practical model we could build would analyze operational vs. non-operational forces only.

We therefore build aggregate and subspecialty-level (operational vs. non-operational) models to obtain a description of the Navy Nurse Corps (NC) system and address the institutional issue of imbalance in the NC's operational and non-operational force structures, respectively. To conduct NC analysis we obtain from the DMDC and BUPERS for FY10-18; the variables we use include ranks from Ensign (O1) through Captain (O6) and all 19 subspecialties (SSPs), including all three subspecialties that an NC officer maintains in her record. To lower the operational liabilities, we exclude any of the critical wartime codes that had suffixes indicating training (T), less than one year of competency (E), and only completed vocational studies (V).

Using remedial actions, we validate both models by Sales' 'goodness of fit' method. To accomplish the highest level of goodness of fit validity while not endangering a loss of too much sample, we include data for two years to build the aggregate level model. For the subspecialty level model, we used four years of data to capture enough sample size for some smaller subspecialty and rank categories.

Despite the smaller sample size in building our model, both models demonstrate high reliance on the accuracy of forecasting capabilities. Per the FY25's benchmark of total authorized billet (BA), 2677, as discussed in Chapter V, Figure 5 (p. 28), our modeling forecasts that the demand for operational force rises, while the non-operational force falls, Figure 10 (p. 37). Per MedMACRE's estimates, shown in Figure 4, the NC's BA by FY25 will probably experience 303 billets loss. This loss is mainly due to the realignment of the DoD medical services under the DHA, described in Chapter II. We discuss how that realignment will likely increase the need for operational forces, while the need for non-operational forces will decrease. Therefore, all those estimated losses shown in Figure 4 would likely occur from the non-operational forces. Our model estimate is in sync with this notion of vertical movement between the operational and non-operational demands—vertical movement in a sense that our demand for the operational rises while the demand for the non-operational forces falls.

Provided that DMDC is merged with the BUPERS data we used to model our $\mathbf{P}_{ssp}$ and data we used to calculate our vector, **r,** is a close representation of a true NC population, we are comfortable with our approach to forecast both the operational and the accession target goals.

B. ASSESSMENT OF THE MODEL AND RECOMMENDATIONS FOR FUTURE WORK

We build our transition matrix, $\mathbf{P}_{ssp}$, to incorporate all three subspecialties 1, 2, and 3 held by an NC. However, per Navy Subspecialty System OPNAVINST 1523, Part B (Office of the Chief of Naval Operations, 2015). Subspecialty 3 could require a lengthy refresher training before the NC is treated as operationally ready—perhaps as long as the lengthy training undertaken by new graduates, whom we exclude from the operational readiness inventory. Therefore, it may be wise to exclude Subspecialty 3 while building the $\mathbf{P}_{ssp}$ to accurately represent current operational readiness inventories.

Furthermore, in the absence of an accurate number for both the total E/S target and specific E/S targets for operational and non-operational forces, our prediction is not expected to provide accurate estimates of the operational forces and accession goals, as our estimates are based on a fixed distributional ratio of operational and non-operational forces from year to year. This nature of fixed distribution is unlikely in the real world of operation. However, the model does provide flexibility to adjust all the applicable constraints.

Recommendations for future research include studying at least two other behaviors of the NC system using same data: (1) build a model to analyze policies or programs from the point of start to their wastage, i.e., absorbing states—for example, examining the effectiveness of NC Accession Training Programs by assessing NCs' likelihood of completing school and eventually getting commissioned, then either retiring or attriting; and (2) provide sufficient data that captures enough observations for each subspecialty, build a model to study each subspecialty level, which would allow forecasting operational forces by specific SSPs.

In addition, during a discussion with the senior NC Manpower practitioners, it was made clear that the DMDC data differs from the BUMIS data. BUMIS data could be used to analyze and compare with this work. This data is managed by BUMED and could therefore more accurately represent the characteristics of the NC community.

The adjustable Markov models that we developed in this thesis provide the Navy NC a Manpower Planning tool that can enhance manpower planning and resource allocation under uncertainty.

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